The Berlin Brain-Computer Interface*

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1 Introduction

The Berlin Brain-Computer Interface (BBCI) uses a machine learning approach to extract subject-specific patterns from high-dimensional EEG-features optimized for revealing the user's mental state. Classical BCI application are brain actuated tools for patients such as prostheses (see Section 4.1) or mental text entry systems ([2] and see [3–6] for an overview on BCI). In these applications the BBCI uses natural motor competences of the users and specifically tailored pattern recognition algorithms for detecting the user's intent. But beyond rehabilitation, there is a wide range of possible applications in which BCI technology is used to monitor other mental states, often even covert ones (see also [7] in the fMRI realm). While this field is still largely unexplored, two examples from our studies are exemplified in Section 4.3 and 4.4.

1.1 The Machine Learning Approach

The advent of machine learning (ML) in the field of BCI has led to significant advances in real-time EEG analysis. While early EEG-BCI efforts required neurofeedback training on the part of the user that lasted on the order of days, in ML-based systems it suffices to collect examples of EEG signals in a so-called *calibration measurement* during which the user is cued to perform repeatedly anyone of a small set of mental tasks. This data is used to adapt the system to the specific brain signals of each user (*machine training*). This step of adaption seems to be instrumental for effective BCI performance due to a large inter-subject variability with respect to the brain signals ([8]). After this preparation step, which is very short compared to the subject training in the operant conditioning approach ([9,10]), the feedback application can start. Here, the users can actually transfer information through their brain activity and control applications. In this phase, the system is composed of the classifier that discriminates between different mental states and the control logic that translates the classifier output into control signals, e.g., cursor position or selection from an alphabet.

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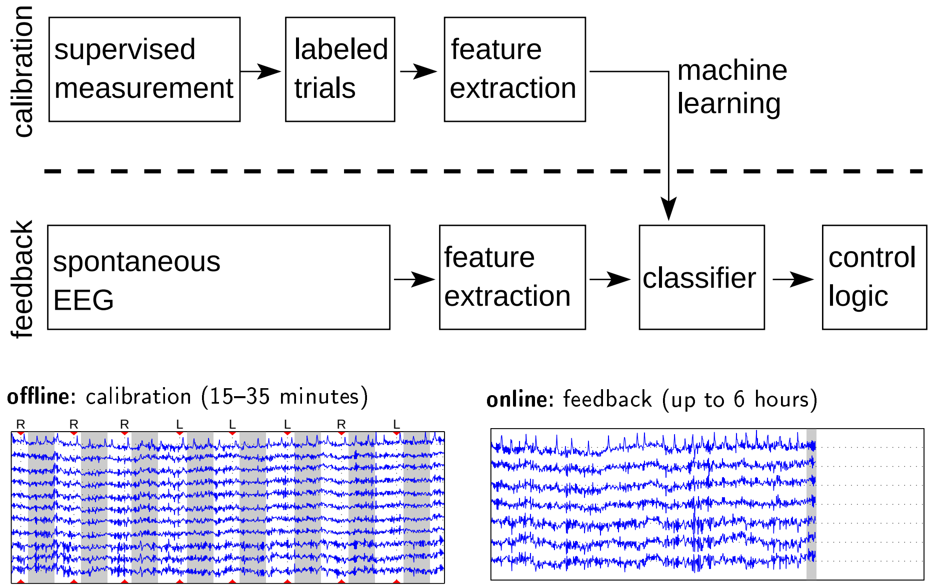

Fig. 1. Overview of the machine-learning-based BCI system. The system runs in two phases. In the calibration phase, we instruct the subjects to perform certain tasks and collect short segments of labeled EEG (trials). We train the classifier based on these examples. In the feedback phase, we take sliding windows from continuous stream of EEG; the classifier outputs a real value that quantifies the likeliness of class membership; we run a feedback application that takes the output of the classifier as input. Finally the subject receives the feedback on the screen as, e.g., cursor control.

An overview of the whole process in an ML-based BCI is sketched in Fig. 1. Note that in alternative applications of BCI technology (see Section 4.3 and 4.4), the calibration may need novel nonstandard paradigms, as the sought-after mental states (like lack of concentration, specific emotions, workload) might be difficult to induce in a controlled manner.

1.2 Neurophysiological Features

Readiness Potential Event-related potentials (ERPs) are transient brain responses that are time-locked to some event. This event may be an external sensory stimulus or an internal state signal, associated with the execution of a motor, cognitive, or psychophysiologic task. Due to simultaneous activity of many sources in the brain, ERPs are typically not visible in single trials (i.e., the segment of EEG related to *one* event) of raw EEG. For investigating ERPs, EEG is acquired during many repetitions of the event of interest. Then short segments (called epochs or trials) are cut out from the continuous EEG signals around each event and are averaged across epochs to reduce event-unrelated

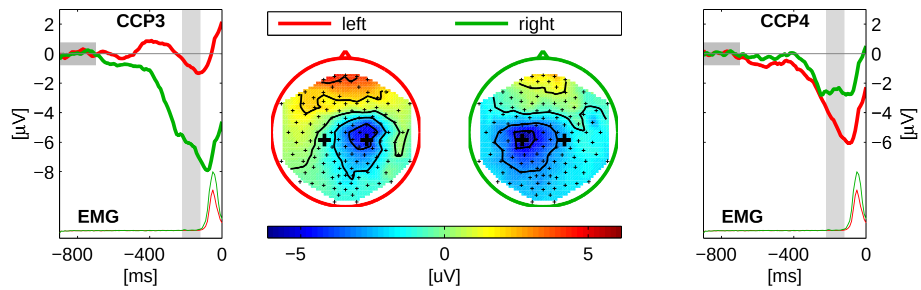

Fig. 2. Response *averaged* event-related potentials (ERPs) of a right-handed subject in a left vs. right hand finger tapping experiment (N =275 resp. 283 trials per class). Finger movements were executed in a self-paced manner, i.e., without any external cue, using an approximate inter-trial interval of 2 seconds. The two scalp plots show the topographical mapping of scalp potentials averaged within the interval -220 to -120 ms relative to keypress (time interval vertically shaded in the ERP plots; initial horizontal shading indicates the baseline period). Larger crosses indicate the position of the electrodes CCP3 and CCP4 for which the ERP time course is shown in the subplots at both sides. For comparison time courses of EMG activity for left and right finger movements are added. EMG activity starts after -120 ms and reaches a peak of 70 μV at -50 ms. The readiness potential is clearly visible, a predominantly contralateral negativation starting about 600 ms before movement and raising approximately until EMG onset.

background activity. In BCI applications based on ERPs, the challenge is to detect ERPs in single trials.

The *readiness potential* (RP, or Bereitschaftspotential) is an ERP that reflects the intention to move a limb, and therefore precedes the physical (muscular) initiation of movements. In the EEG it can be observed as a pronounced cortical negativation with a focus in the corresponding motor area. In hand movements the RP is focussed in the central area contralateral to the performing hand, cf. [11–13] and references therein for an overview. See Fig. 2 for an illustration. Section 4.2 shows an application of BCI technology using the readiness potential. Further details about our BCI-related studies involving RP can be found in [8,14–16].

Sensorimotor Rhythms Apart from transient components, EEG comprises rhythmic activity located over various areas. Most of these rhythms are so-called idle rhythms, which are generated by large populations of neurons in the respective cortex that fire in rhythmical synchrony when they are not engaged in a specific task. Over motor and sensorimotor areas in most subjects oscillations with a fundamental frequency between 9 and 13 Hz can be observed, the so called μ-rhythm. Due to its comb-shape, the μ-rhythm is composed of several harmonics, i.e., components of double and sometimes also triple the fundamental frequency ([17]) with a fixed phase synchronization, cf. [18]. These sensorimotor rhythms (SMRs) are attenuated when engagement with the respective limb takes place. As this effect is due to loss of synchrony in the neural populations, it is termed event-related desynchronization (ERD), see [19]. The increase of oscillatory EEG (i.e., the reestablishment of neuronal synchrony after the event) is called event-related synchronization (ERS). The ERD in the motor and/or sensory cortex can be observed even when a subject is only thinking of a movement or imagining a sensation in the specific limb. The strength of the sensorimotor idle rhythms as measured by scalp EEG is known to vary strongly between subjects.

Section 3.1 and 3.2 show results of BCI control exploiting the voluntary modulation of sensorimotor rhythm.

Error-Related Potentials It is a well-known finding in human psychophysics that a subject's recognition of having committed a response error is accompagnied by specific EEG variations that can be observed in (averaged) ERPs (e.g. [20]). The ERP after an error trial is characterized by two components: a negative wave called error negativity (N_E) [21] (or error-related negativity (ERN, [22])) and a following broader positive peak labeled as error positivity (P_E), [20]. It has been demonstrated that the P_E is more specific to errors while the N_E can also be observed in correct trials, cf. [20], [23]. Although both amplitude and latency depend on the specific task, the N_E occurs delayed and less intense in correct trials than in error trials. The N_E is also elicited by negative feedback ([24]) and by error observation ([25]). Furthermore [26] investigated error-related potentials in response to errors that are made by an interface in human-computer interaction.

Section 3.3 investigates the detectability of error-related potentials after erroneous BCI feedback, which gives a perspective of the potential use in BCI systems as a 'second-pass' response verification.

2 Processing and Machine Learning Techniques

Due to the simlutaneous activity of many sources in the brain and additional influence by noise the detection of relevant components of brain activity in single trials as required for BCIs is a data analytical challenge. One approach to compensate for the missing opportunity to average across trials is to record brain activity from many sensors and to exploit the multi-variateness of the acquired signals, i.e., to average across space in an intelligent way. Raw EEG scalp potentials are known to be associated with a large spatial scale owing to volumne conduction ([27]). Accordingly all EEG channels are highly correlated and powerful spatial filters are required to extract localized information with a good signal to noise ratio (see also the motivation for the need of spatial filtering in [28]).

In the case of detecting ERPs, such as RP or error-related potentials, the extraction of features from one source is mostly done by linear processing methods. In this case the spatial filtering can be acomplished implicitly in the classification step (interchangability of linear processing steps). For the detection of modulations of SMRs, the processing is non-linear (e.g. calculation of band power). In this case, the prior application of spatial filtering is extremely beneficial. The methods used for BCIs range from simple fixed filters like Laplacians ([29]), and data driven unsupervised techniques like independent component analysis (ICA) [30] or model based approaches ([31]) to data driven supervised techniques like common spatial patterns analysis (CSP) [28].

In this Section we summarize the two techniques that we consider most important for classifying multi-variate EEG signals, CSP and regularized linear discriminant analysis. For a more complete and detailed review of signal processing and pattern recognition techniques see [8,32,33].

2.1 Common Spatial Patterns Analysis

The CSP technique (see [34]) allows to determine spatial filters that maximize the variance of signals of one condition and at the same time minimize the variance of signals of another condition. Since variance of band-pass filtered signals is equal to band-power, CSP filters are well suited to detect amplitude modulations of sensorimotor rhythms (see Section 1.2) and consequently to discriminate mental states that are characterized by ERD/ERS effects. As such it has been well used in BCI systems ([14,35]) where CSP filters are calculated individually for each subject on the data of a calibration measurement.

The CSP technique decomposes multichannel EEG signals in the sensor space. The number of spatial filters equals the number of channels of the original data. Only few filters have properties that make them favorable of classification. The discriminative value of a CSP filter is quantified by its generalized eigenvalue. This eigenvalue is relative to the sum of the variances in both conditions. An eigenvalue of 0.9 for class 1 means an average ratio of 9:1 of variances during condition 1 and 2. See Fig. 3 for an illustration of CSP filtering.

For details on the technique of CSP analysis and its extensions we refer to ([28,36–39]).

2.2 Regularized Linear Classification

For known Gaussian distributions with the same covariance matrix for all classes, it can be shown that Linear Discriminant Analysis (LDA) is the optimal classifier in the sense that it minimizes the risk of misclassification for new samples drawn from the same distributions ([40]). Note that LDA is equivalent to Fisher Discriminant and Least Squares Regression ([40]). For EEG classification the assumption of Gaussianity can be achieved rather well by appropriate preprocessing of the data. But the mean and covariance matrix of the distributions have to be estimated from the data, since the true distributions are not known. Especially for high-dimensional data with few trials the estimation of the covariance matrix is very imprecise, because the number of unknown parameters is quadratic in the number of dimensions. In the estimation of covariance matrices this leads to a systematic error: Large eigenvalues of the original covariance

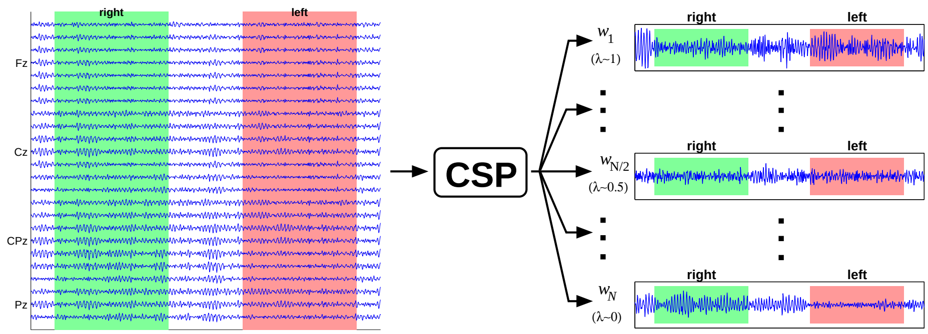

Fig. 3. The input the CSP analysis are (band-pass filtered) multi-channel EEG signals which are recorded for two conditions (here 'left' and 'right' hand motor imagery. The reults of CSP analysis is a sequence of spatial filters. The number of filters (here N) is equal to the number of EEG channels. When these filters are applied to the continuous EEG signals, the (average) relative variance in the two conditions is given by the eigenvalues. An eigenvalue near 1 results in large variance of signals of condition 1 and an eigenvalue near 0 reults in small variance for condition 1. Most eigenvalues are near 0.5 such that the corresponding filters do not contribute to the discrimination.

matrix are estimated too large, and small eigenvalues are estimated too small, see Fig. 4. This error in the estimation degrades classification performance (and invalidates the optimality statement for LDA). A common remedy for the systemtic bias, is shrinkage of the estimated covariance matrices (e.g. [41]):

The estimator of the covariance matrix $\hat{\mathbf{\Sigma}}$ is replaced by

$$\tilde{\mathbf{\Sigma}} = (1-\gamma)\hat{\mathbf{\Sigma}} + \gamma\lambda\mathbf{I}$$

for a $\gamma \in [0, 1]$ and λ defined as average eigenvalue trace$(\hat{\mathbf{\Sigma}})/d$ with d being the dimensionality of the feature space and $\mathbf{I}$ being the identity matrix.. Then the following holds. Since $\hat{\mathbf{\Sigma}}$ is positive semi-definite we can have an eigenvalue decomposition $\hat{\mathbf{\Sigma}} = \mathbf{V}\mathbf{D}\mathbf{V}^\top$ with orthonormal $\mathbf{V}$ and diagonal $\mathbf{D}$. Due to the orthogonality of $\mathbf{V}$ we get

$$\tilde{\mathbf{\Sigma}} = (1-\gamma)\mathbf{V}\mathbf{D}\mathbf{V}^\top + \gamma\lambda\mathbf{I} = (1-\gamma)\mathbf{V}\mathbf{D}\mathbf{V}^\top + \gamma\lambda\mathbf{V}\mathbf{I}\mathbf{V}^\top = \mathbf{V}\left((1-\gamma)\mathbf{D} + \gamma\lambda\mathbf{I}\right)\mathbf{V}^\top$$

as eigenvalue decomposition of $\tilde{\mathbf{\Sigma}}$. That means

- $\tilde{\mathbf{\Sigma}}$ and $\hat{\mathbf{\Sigma}}$ have the same Eigenvectors (columns of $\mathbf{V}$)
- extreme eigenvalues (large or small) are modified (shrunk or elongated) towards the average λ.
- $\gamma = 0$ yields unregularized LDA, $\gamma = 1$ assumes spherical covariance matrices.

Using LDA with such modified covariance matrix is termed regularized LDA. The parameter γ needs to be estimated from training data, e.g. by cross validation.

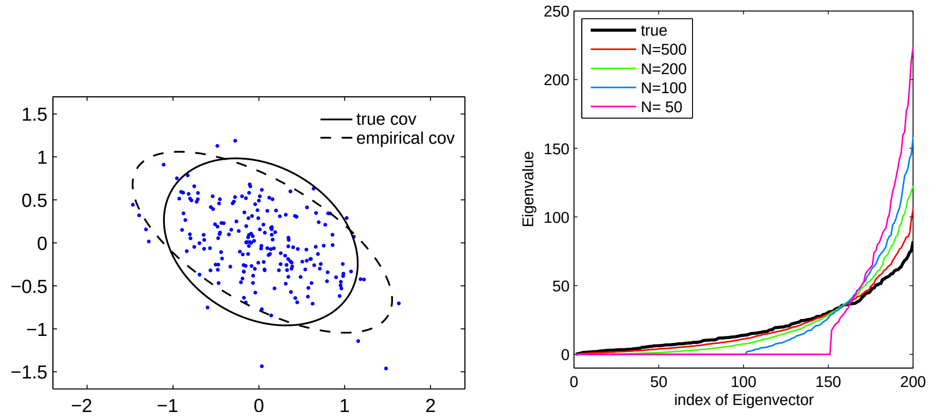

Fig. 4. *Left:* Data points drawn from a Gaussian distribution (gray dots; $d = 200$ dimensions) with true covariance matrix indicated by an ellipsoid in solid line, and estimated covariance matrix in dashed line. *Right:* Eigenvalue spectrum of a given covariance matrix (bold line) and eigenvalue spectra of covarinace matrices estimated from a finite number of samples drawn (N= 50, 100, 200, 500) from a corresponding Gaussian distribution.

3 BBCI Control Using Motor Paradigms

3.1 High Information Transfer Rates

In order to preserve ecological validity (i.e., the correspondence between intention and control effect) we let the users perform motor tasks for applications like cursor movements. For paralyzed patients the control task is to attempt movements (e.g., left hand or right hand or foot), other subjects are instructed to perform kinesthetically imagined movements ([42]) or quasi-movements ([43]).

As a test application of the performance of our BBCI system we implemented a 1D cursor control. One of the two fields on the left and right edge of the screen was highlighted as target at the beginning of a trial, see Fig. 5. The cursor was initially at the center of the screen and started moving according to the BBCI classifier output about half a second after the indication of the target. The trial ended when the cursor touched one of the two fields. That field was then colored green or red, depending on whether or not it was the correct target. After a short period the next target cue was presented (see [8,44] for more details).

The aim of our first feedback study was to explore the limits of possible information transfer rates (ITRs) in BCI systems not relying on user training or evoked potentials. The ITR derived in Shannon's information theory can be used to quantify the information content, which is conveyed through a noisy (i.e., error introducing) channel. In BCI context:

$$\text{bitrate}(p, N) = \left(p \log_2(p) + (1-p) \log_2 \left(\frac{1-p}{N-1} \right) + \log_2(N) \right) \qquad (1)$$

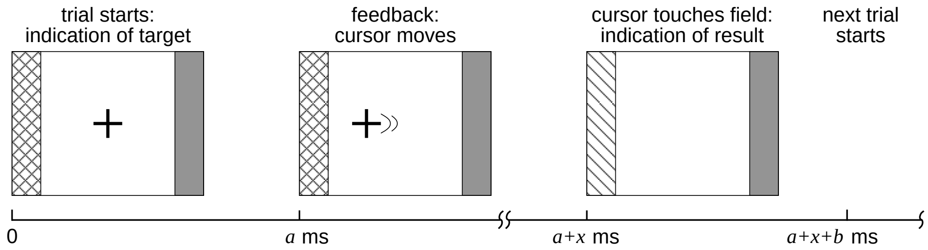

Fig. 5. Course of a feedback trial. The target cue (field with crosshatch) is indicated for a ms, where a is chosen individual according to the capabilities of the user. Then the cursor starts moving according to the BCI classifier until it touches one of the two fields at the edge of the screen. The duration depends on the performance and is therefore different in each trial (x ms). The touched field is colored green or red according to whether its was the correct target or not (for this black and white reproduction, the field is hatched with diagonal lines). After b ms, the next trial starts, where b is chosen indivudally for the subject.

where p is the accuracy of the subject in making decisions between N targets, e.g., in the feedback explained above, $N = 2$ and p is the accuracy of hitting the correct bars. To include the speed of decision into the performance measure:

$$\text{ITR [bits/min]} = \frac{\#\text{ of decisions}}{\text{duration in minutes}} \cdot \text{bitrate}(p, N) \qquad (2)$$

In this form, the ITR takes different average trial durations (i.e., the speed of decisions) and different number of classes into account. Therefore, it is often used as a performance measure of BCI systems ([45]). Note, that it gives reasonable results only if some assumptions on the distribution of error are met, see [46].

The subjects of the study ([8,14]) were 6 staff members, most of which had performed feedback with earlier versions of the BBCI system before. (Later, the study was extended by 4 further subjects, see [44]). First the parameters of preprocessing were selected and a classifier was trained based on a calibration measurement individually for each subject. Then feedback was switched on and further parameters of the feedback were adjusted according to the subject's request.

For one subject, no significant discrimination between the mental imagery conditions was found, see [44] for an analysis of that specific case. The other five subjects performed 8 runs of 25 cursor control trials as explained above. Table 1 shows the performance result in accuracy (percentage of trials in which the subject hit the indicated target) and as ITR (see above). As a test of practical usability, subject *al* operated a simple text entry system based on BBCI cursor control. In a free spelling mode, he spelled 3 German sentences with a total of 135 characters in 30 minutes, which is a spelling speed of 4.5 letters per minutes. Note that the subject corrected all errors using the deletion symbol. For details, see [47]. Recently, using the novel mental text entry system Hex-o-Spell which was developed in cooperation with the Human-Computer Interaction Group at

Table 1. Results of a feedback study with 6 healthy subjects (identification code in the first column). From the three classes used in the calibration measurement the two chosen for feedback are indicated in second column (L: left hand, R: right hand, F: right foot). The accuracies obtained online in cursor control are given in column 3. The average duration $\pm$ standard deviation of the feedback trials is provided in column 4 (duration from cue presentation to target hit). Subjects are sorted according to feedback accuracy. Columns 5 and 6 report the information transfer rates (ITR) measured in bits per minute as obtained by Shannon's formula, cf. (1). Here the complete duration of each run was taken into account, i.e., also the inter-trial breaks from target hit to the presentation of the next cue. The column *overall ITR* (oITR) reports the average ITR of all runs (of 25 trials each), while column *peak ITR* (pITR) reports the peak ITR of all runs.

subject	**classes**	**accuracy [%]**	**duration [s]**	**oITR [b/m]**	**pITR [b/m]**
al	LF	98.0 ± 4.3	2.0 ± 0.9	24.4	35.4
ay	LR	95.0 ± 3.3	1.8 ± 0.8	22.6	31.5
av	LF	90.5 ± 10.2	3.5 ± 2.9	9.0	24.5
aa	LR	88.5 ± 8.1	1.5 ± 0.4	17.4	37.1
aw	RF	80.5 ± 5.8	2.6 ± 1.5	5.9	11.0
mean		90.5 ± 7.6	2.3 ± 0.8	15.9	27.9

the University of Glasgow, the same subject achieved a spelling speed of more than 7 letters per minute, cf. [2,48].

3.2 Good Performance without Subject Training

The goal of our second feedback study was to investigate for what proportion of naive subjects our system could provide successful feedback in the very first session ([49]). The design of this study was similar to the one described above. But here the subjects were 14 individuals who never performed in a BCI experiment before. Furthermore the parameters of the feedback have been fixed beforehand for all subjects to conservative values.

For one subject no distinguishable classes were identified. The other 13 subjects performed feedback: 1 near chance level, 3 with 70-80%, 6 with 80-90% and 3 with 90-100% hits. The results of all feedbacks runs are shown in Fig. 6.

This clearly shows that a machine learning based approach to BCI such as the BBCI is able to let BCI novices perform well from the first session. Note that in all BCI studies – independent of whether machine learning is used or not – non-performing subjects are encountered (e.g. [50]). It is an open problem how to alleviate this issue.

3.3 Automatic Response Verification

An elegant approach to cope with BCI misclassifications is a response checking mechanism that is based on the subject's brain signals themselves. This ap-

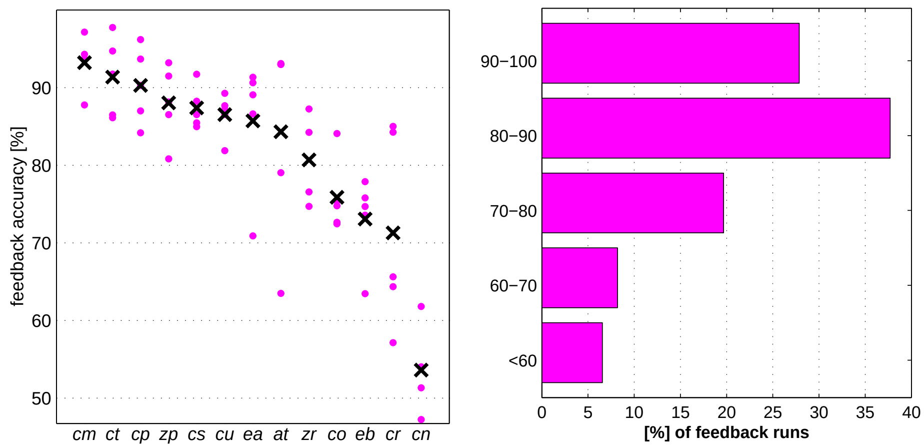

Fig. 6. *Left:* Feedback accuracy of all runs (gray dots) and intra-subject averages (black crosses). *Right:* Histogram of accuracies obtained in BBCI-controlled cursor movement task in all feedback runs of the study.

proach was first explored in [51] in an offline analysis of BCI feedback data. A simple amplitude threshold criterium for the detection of error-related potentials was used to demonstrate the potential use of the approach. Several studies have shown the possibility to detect error-related potentials in choice reaction tasks ([16,52,53]) with more advanced pattern recognition algorithms. The results taken together give a clear indication that a response verification might be a worthwhile add-on to BCIs in the following sense of a two-pass system. We call the original classification of the BCI feedback first-pass. Then in the second-pass, the interval after the response feedback is subjected to the error potential detector. If that indicates that the user perceived the feedback as an error, the decision is rejected[4] . Surprisingly, so far no online BCI application with error-detection was reported. Nevertheless, further important evidence was provided in [26,54] by showing the detecability of potentials elicited by interaction errors in a simulated BCI. But due to the discrete feedback with fixed timing used in that study, it remains open how the situation would be in a continuous cursor control feedback where an upcoming error might be anticipated by the users by predictions about the cursor movement (e.g., no classical phasic error-related component might be elicited when the cursor starts moving slowly towards the wrong field).

Fig. 7 shows the ERPs for correct and erroneous feedback trials with respect to time point $t = 0$ when the cursor enters either the correct or the wrong field (for the design of the feedback, see Fig. 5). In this subject the error-related pos-

[4] In binary decisions the outcome could even be reverted. But practically it was observed that such a strategy leads to less improvement if the error detection itself is also error prone ([54]).

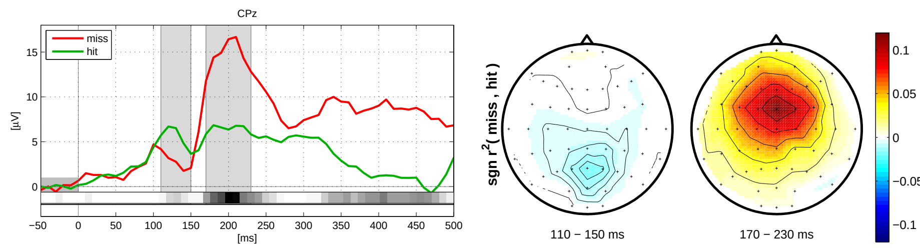

Fig. 7. *Left:* ERPs for correct and erroneous feedback trials. *Right:* Topography of signed r^2 values for the time intervals of error-related negativity (110 to 150 ms) and error-related positivity (170 to 230 ms).

itivity as well as the error-related negativity is clearly visible at fronto-central and parieto-central scalp position. In other subjects often only the positive component was observed. It can be speculated that the shorter negative component is obscured by the jitter on the time point of error recognition owing to the feedback paradigm (see remark above). This issue is subject of an ongoing investigation.

In order to quantify the potential gain of an automatic error rejection, we calculate the bitrate of a two-pass BCI system as outlined above. Let tp be the rate of true positives (erroneous trials, classified as errors) and tn the rate of true negatives (correct trials, classified as correct). Then we can calculated the bitrate of a system that rejects trials which were classified as errors in the following way ([54]):

$$\begin{aligned} r_{\text{accepted}} &= p\,tn + (1-p)(1-tp) && \text{rate of accepted trials} \\ p_{\text{accepted}} &= p\frac{tn}{r_{\text{accepted}}} && \text{accuracy on accepted trials} \\ \text{bitrate}_{\text{rv}}(p, tp, tn, N) &= \text{bitrate}(p_{\text{accepted}}, N) && (3) \end{aligned}$$

Fig. 8 shows the improvement in ITR that would have been achieved by using the response verification with rejecting decision for trials which were classified as erroneous. The relative gain obtained through response verification is 80 % on average for the worse performing subjects and 25 % for better performing subjects.

4 Applications of BBCI Technology

Subsequently we will discuss BBCI applications for rehabilitation (prosthetic control and spelling [2,3,48]) and *beyond* (gaming, mental state monitoring [55, 56] etc.). Our view is that the development of BCI to enhance man machine interaction for the healthy will be an important step to broaden and strengthen the future development of neurotechnology.

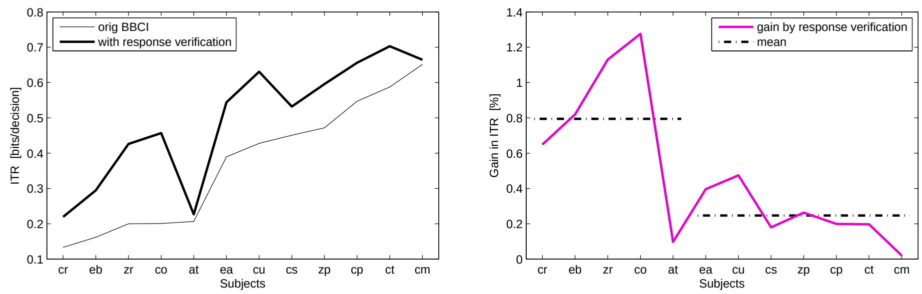

Fig. 8. *Left:* Bitrates (Eq. (1)) of original BCI classification (thin line) and calculated bitrates (Eq. (3)) for the case that trials are rejected which are classified as errors by the error-potential detector (thick line). Only those subjects are taken into this investigation who committed at least 20 error and had above chance performance. *Right:* Relative gain obtained through response verification. The mean for the worse performing subjects is 80 % and the mean for better performing subjects is 25 %.

4.1 Prosthetic Control

Motor-intention based BCI offers the possibility of a direct and intuitive control modality for persons disabled by high-cervical spinal cord injury, i.e., tetraplegics, whose control of all limbs is severely impaired. The advantage of this type of BCI over other interface modalities is that by directly translating movement intention into a command to a prosthesis, the link between cortical activity related to motor control of the arm and physical action is restored, thereby offering a possible rehabilitation function, as well as enhanced motivation factor for daily use. Testing of this concept is the main idea driving the Brain2Robot project (see Acknowledgement). However, two important challenges must be fully met before non-invasive, EEG based motor imagery BCI can be practically used by the disabled.

One such challenge is the cumbersome nature of standard EEG set-up, involving application of gel, limited recording time, and subsequent removal of the set-up, which involves washing the hair. It is unlikely that disabled persons, in need of BCI technology for greater autonomy, would adopt such a system. Meanwhile, short of any invasive or minimally invasive recording modality, the only available option is the use of so called ‘dry’ electrodes, i.e. not requiring the use of conductive gel or other liquids in such a way that electrode application and removal takes place in a matter of minutes. We have developed such technology (a ‘dry cap’) and tested it for motor-imagery based BCI [57]. The cap required about 5 minutes for set-up and exhibited an average of 70 % of the information transfer rate achieved for the same subjects with respect to a standard EEG ‘gel cap’, the difference being most likely attributed to the use of 6 electrodes used in the dry cap vs. 64 electrodes used in the gel cap. Although the locations of the 6 electrodes were chosen judiciously (by analyzing which electrode positions in the gel cap were most important, as expected 3 electrodes over each cortical motor area), some performance degradation was unavoidable and necessary – a full 64 electrode dry cap would also be cumbersome.

Another challenge for EEG-BCI control of prosthetics is inherent safety. This is of paramount importance, whether the prosthetic controlled is an orthosis (a worn mechanical device which augments the function of a set of joints) or a robot (which may move the paralysed arm or be near the body but unattached to it, as in the case of Brain2Robot), or even a neuroprosthesis, i.e. a system which electrically activates muscles in the user's arm or peripheral neurons which innervate these muscles. Specifically, the BCI interface should not output spurious or unintended action commands to the prosthetic device, as these could cause injuries, or even in the case in which the probability of injury is low and secondary safety 'escape commands' are incorporated, it may (reasonably) cause fear in the otherwise immobile user and therefore discourage him or her from continuing to use the system. Therefore we have looked at necessary enhancements to commonly used 'BCI feedback' control which could incorporate the use of a 'rest' or 'idle' state, i.e. a continuous output of the classifier which not only outputs a command related to a trained brain state (say, imagination of left hand movement) but a 'do nothing' command related to a state in which the user performs daily activities unrelated to motor imagination (a 'rest' or 'idle' state) and in which the prosthetic should do nothing. Thus we have begun to look at the trade-off between speed of BCI (information transmission rate or ITR) and safety (false positive rate) achievable by incorporating a 'control' law, which is a differential equation whose inputs are continuous outputs of the classifer, in our case a quadratic-type classifier, and whose output is the command to the prosthetic ([58]). It remains to be seen how much each particular subject, whose 'standard' BCI performance varies greatly, must trade reduced speed for increased safety.

A final implicit goal of all BCI research is to improve the maximally achievable ITR for each type of brain imaging modality. In the case of EEG the ITR is seems to be limited to about 1 decision every 2 seconds ([44], fastest subject performed at an average speed of 1 binary decision every 1.7 s) despite intensive research effort to improve it. In the case of Brain2Robot further information about the desired endpoint of arm movement is obtained by 3D tracking of gaze – eye movement and focus being normally intact in the tetraplegic population, and the achievable ITR is sufficient, since it lies in the range of the frequency of discrete reaching movements of the hand. However, competing issues of cognitive load, safety and achievable dexterity can only be assessed by testing BCI for prosthetic control with the intended user group while paying attention to the level of disability and motor-related EEG patterns in each subject, as both are likely to vary significantly.

4.2 Time-critical Applications: Prediction of Upcoming Movements

In time-critical control situations, BCI technology might provide early detection of reactive movements based on preparatory signals for the reduction of the time span between the generation of an intention (or reactive movements) and

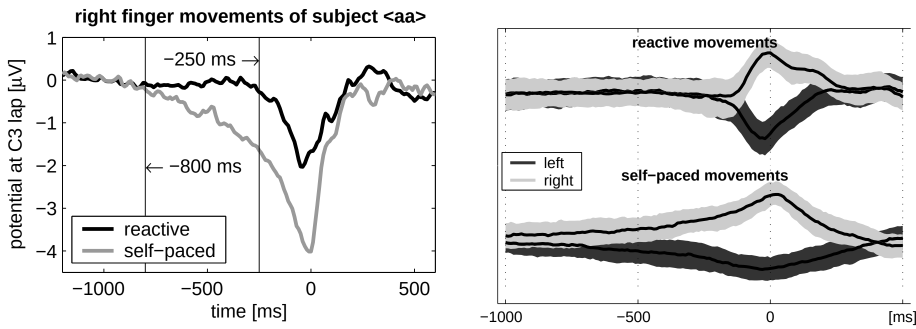

Fig. 9. *Left:* Averaged readiness potential in spontaneous selfpaced (grey) and reactive (dark) finger movements (with $t = 0$ at key press) for one subject. *Right:* Distribution of the continuous classifier output in both experimental settings.

the onset of the intended technical operation (e.g. in driver-assisted measures for vehicle safety). Through detection of particularly early readiness potentials (see Section 1.2) which reflect the mental preparation of movements, control actions can be prepared or initiated before the actual movement and thus we intend to decode these signals in a very timely and accurate manner.

In order to explore the prospective value of BCI for such applications, we conducted a two alternative forced choice experiment (d2-test), in which the subject had to respond as fast as possible with a left or right index finger key press, see [59]. Fig. 9 (left) compares the readiness potentials in such reactive finger movements with those in selfpaced finger movements ($t = 0$ for key press). Fig. 9 (right) shows the traces of continuous classifier output for reactive (upper subplot) and selfpaced (lower subplot) finger movements. As expected, the discrimination between upcoming left vs. right finger movements is better possible for the self-paced movements at an *early* stage, but towards the time point of key press performance is similar. In particular, 100 ms before the keypress even for movements in fast reations, a separation becomes substantial. The discriminability already at this point in time confirms the potential value of BCI technology for time-critical applications. For more details and classification results, we refer the interested reader to [59].

4.3 Neuro Usability

In the development of many new products or in the improvement of existing products, usability studies play an important role. They are performed in order to measure to what degree a product meets the intended purpose with regard to the aspects effectiveness, efficiency and user satisfaction.A further goal is to quantify the joy of use. While effectiveness can be quantified quite objectively, e.g., in terms of task completion, the other aspects are more intricate to assess. Even psychic variables consciously unaccessible to the persons themselves might be involved. Furthermore, in usability studies it is of interest to perform an effortless continuous acquistion of usability parameters whilst not requiring any action on the side of the subject as this might interfer with the task at hand. For these reasons, BCI technology could become a crucial tool for usability studies in the future.

We exemplify the potential benefit of BCI technology in one example ([55]). Here, usability of new car features is quantified by the mental workload of the car driver. In the case of a device that uses fancy man-machine interface technology, the producer should demonstrate that it does not distract the driver from the traffic (mental workload is not increased when the feature is used). In case of a tool for which the manufacturer claims it relieves the driver from workload (e.g., automatic distance control), this effect should be demonstrated as objectively as possible.

Since there is no ground truth available on the cognitive workload to which the driver is exposed, we designed a study[5] in which additional workload was induced in a controlled manner. For details, please refer to [55]. EEG was acquired from 12 male and 5 female subjects while driving on a highway at a speed of 100 km/h (primary task). Second, the subjects had an auditory reaction task: one of two buttons mounted on the left and right index finger had to be hit every 7.5 s according to a given vocal prompt. For the tertiary task, two different conditions have been used. (a) mental calculation; (b) following one of two simultaneously broadcast voice recordings. In a first a calibration phase, the developed BBCI workload detector was adapted to the individual driver. After that, the system was able to predict the cognitive workload of the driver online. This information was used in the test phase to switch off the auditory reaction task, when high workload was detected ('mitigation').

As a result of the mitigation strategy, the average reaction time in the test phase was on average 100 ms faster than in the (un-mitigated) calibration phase ([55]). Since in total the workload during the two phases has been equal, it can be conjectured that the average reactivity was the same. Thus, the difference in reaction times can only be explained by the fact that the workload detector switched off the reaction task during periods of reduced reactivity.

Note, that the high intersubject variabiltiy, which is a challenge for many BCI applications comes as an advantage here: for neuro-usability studies, top subjects (with respect to the detectability of relevant EEG components) of a study can be selected according to the appropriateness of their brain signals.

Beyond the neuro usability aspect of the study, one could speculate that such devices might be incorporated in future cars in order to reduce distractions (e.g., navigation system is switched off during periods of high workload) to a minimum when the drivers' brain is already over-loaded by other demands during potentially hazardous situations.

[5]This study was performed in cooperation with the Daimler AG. For further information, please refer to [55].

4.4 Mental State Monitoring

When aiming to optimize the design of user interfaces or, more general, of a work flow, the mental state of a user during the task execution can provide useful information. This information can not only be exploited for the improvement of BCI applications, but also for improving industrial production environments, the user interface of cars and for many other applications. Examples of these mental states are the levels of arousal, fatigue, emotion, workload or other variables whose brain activity correlates (at least partially) are amenable to measurement. The improvement of suboptimal user interfaces reduces the number of critical mental states of the operators. Thus it can lead to an increase in production yield, less errors and accidents, and avoids frustration of the users.

Typically, information collected about the mental states of interest is exploited in an offline analysis of the data and leads to a re-design of the task or the interface. In addition, it might be desirable that a method for mental state monitoring can be applied online during the execution of a task. Traditional methods for capturing mental states and user ratings are questionnaires, video surveillance of the task, or the analysis of errors made by the operator. However questionnaires are of limited use for precisely assessing the information of interest as the delivered answers are often distorted by subjectiveness. Questionnaires cannot determine the quantities of interest in real-time (during the execution of the task) but only in retrospect; moreover, they are intrusive i.e. they interfere with the task. Even the monitoring of eye blinks or eye movements only allows for an indirect access to the user's mental state. Although the monitoring of a user's errors is a more direct measure, it detects critical changes of the user state post-hoc only. Neither is the anticipation of an error possible, nor can suitable countermeasures be taken to avoid it.

As a new approach we propose the use of EEG signals for mental state monitoring and combine it with BBCI classfication methods for data analysis. With this approach the brain signals of interest can be isolated from background activity as in BCI systems; this combination allows for the non-intrusive evaluation of mental states in real-time and on a single-trial basis such that an online system with feedback can be build.

In a pilot study ([56]) we evaluated the use of EEG signals for arousal monitoring. The experimental setting simulates a security surveillance system where the sustained concentration ability of the user in a rather boring task is crucial. As in BCI, the system had to be calibrated to the individual user in order to recognize and predict mental states, correlated with attention, task involvement or a high or low number of errors of the subject respectively.

Experimental Setup for Attention Monitoring In this study a subject was seated approx. 1 m in front of a computer screen that displayed different stimuli in a forced choice setting. She was asked to respond quickly to stimuli by pressing keys of a keyboard with either the left or right index finger; recording was done with a 128 channel EEG at 100 Hz. The subject had to rate several hundred x-ray images of luggage objects as either dangerous or harmless by a key press after each presentation. The experiment was designed as an oddball paradigm where the number of the harmless objects was much larger than that of the dangerous objects. The terms standard and deviant will subsequently be used for the two conditions. One trial was usually performed within 0.5 seconds after the cue presentation.

The subject was asked to perform 10 blocks of 200 trials each. Due to the monotonous nature of the task and the long duration of the experiment, the subject was expected to show a fading level of arousal which results in worse concentration and the generation of more and more erroneous decisions during later blocks.

For the offline analysis of the collected EEG signals, the following steps were applied. After exclusion of channels with bad impedances a spatial Laplace filter was applied and the band power features from 8-13 Hz were computed on 2 s windows. The resulting band power values of all channels were concatenated into a final vector. As the subject's correct and erroneous decisions were known, a supervised LDA classifier was trained on the data. The classification error of this procedure was estimated by a cross-validation scheme that left out a whole block of 200 trials during each fold for testing. As the number of folds was determined by the number of experimental blocks it varied slightly from subject to subject.

Results The erroneous decisions taken by a subject were recorded and smoothed in order to form a measure for the arousal. This measure is further referred to as *error index* and reflects the ability of the subject to concentrate and fulfill the security task. To enhance the contrast of the discrimination analysis, two thresholds were introduced for the error index and set after visual inspection. Extreme trials outside these thresholds defined two sets of trials with a rather high rsp. a low value. The EEG data of the trials were labeled as *sufficiently concentrated* or *insufficiently concentrated* depending on these thresholds for later analysis. Fig. 10 shows the error index. The subject did perform nearly error-free during the first blocks but then showed increasing errors beginning with block 4. However, as the blocks were separated by short breaks, the subject could regain attention at the beginning of each new block at least for a small number of trials. The trials of high and low error index formed the training data for teaching a classifier to discriminate mental states of insufficient arousal based on single trial EEG data.

A so-called Concentration Insufficiency Index (CII) of a block was generated by an LDA classifier that had been trained off-line on the labeled training data of the remaining blocks. The classifier output (CII) of each trial is plotted in Fig. 10 together with the corresponding error index. It can be observed that the calculated CII mirrors the error index for most blocks. More precisely the CII mimics the error increase inside each block and in blocks 3 and 4 it can anticipate the increase of later blocks, i.e. out-of-sample. For those later blocks the CII reveals that the subject could not recover its full arousal during the

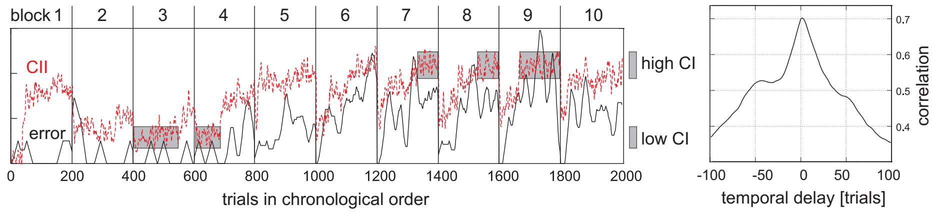

Fig. 10. *Left*: Comparison of the concentration insufficiency index (CII, dotted curve) and the error index for the subject. The error index (the true performed errors smoothed over time) reflects the inverse of the arousal of the subject. *Right*: Correlation coefficient between the CII (returned by the classifier) and the true performance for different time shifts. Highest correlation is around a zero time shift as expected. Please note that the CII has an increased correlation with the error even before the error appears.

breaks. Instead it shows a short-time arousal for the time immediately after a break, but the CII accumulates over time.

The correlation coefficient of both time series with varying temporal delay is shown in the right plot of Fig. 10. The CII inferred by the classifier and the errors that the subject had actually produced correlate strongly. Furthermore the correlation is high even for predictions that are up to 50 trials ahead into the future.

For a physiological analysis please refer to the original paper [56].

5 Conclusion

The chapter provides a brief overview on the Berlin Brain-Computer Interface. We would like to emphasize that the use of modern machine learning tools – as put forward by the BBCI group – is pivotal for a successful and high ITR operation of a BCI from the first session [44,49]. Note that due to space limitations the chapter can only discuss general principles of signal processing and machine learning for BCI; for details ample references are provided (see also [3]). Our main emphasis was to discuss the wealth of applications of neurotechnology beyond rehabilitation. While BCI is an established tool for opening a communication channel for the severely disabled ([60–64], its potential as an instrument for enhancing man-machine interaction is underestimated. The use of BCI technology as a direct channel additional to existing means to communicate opens applications in mental state monitoring [55,56], gaming [65,66], virtual environment navigation[67], vehicle safety [55], rapid image viewing [68] and enhanced user modeling. To date only proofs of concept and first steps have been given that still need to move a long way to innovative products, but already the attention monitoring and neuro usability applications outlined in Section 4.3 and 4.4 show the usefulness of neurotechnology for the monitoring of complex cognitive mental states. With our novel technique at hand, we can make direct use of mental state monitoring information to enable Human-Machine Interaction to exhibit adaptive anticipatory behaviour.

To ultimately succeed in these promising applications the BCI field needs to proceed in multiple aspects: (a) improvement of EEG technology beyond gel electrodes and (e.g. [57]) towards cheap and portable devices, (b) understanding of the BCI-illiterates phenomenon, (c) improved and more robust signal processing and machine learning methods, (d) higher ITRs for non-invasive devices and finally (e) the development of compelling industrial applications also outside the realm of rehabilitation.

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